Pedestrian detection at 100 frames per second

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VISICS

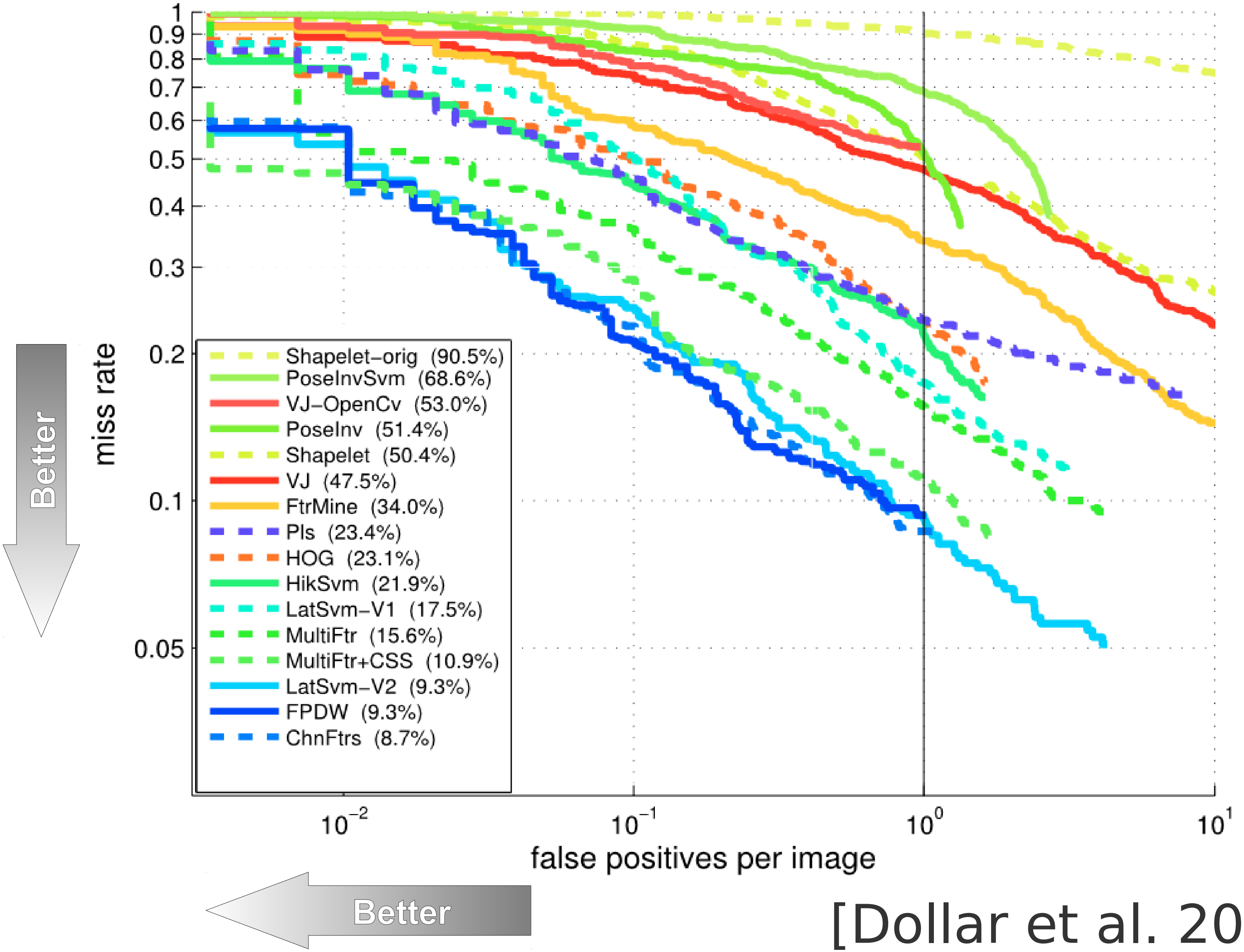
Why 100 fps ?

- Detection is one module amongst many
- Less computational power
- *Latency matters*

How can we make things faster ?

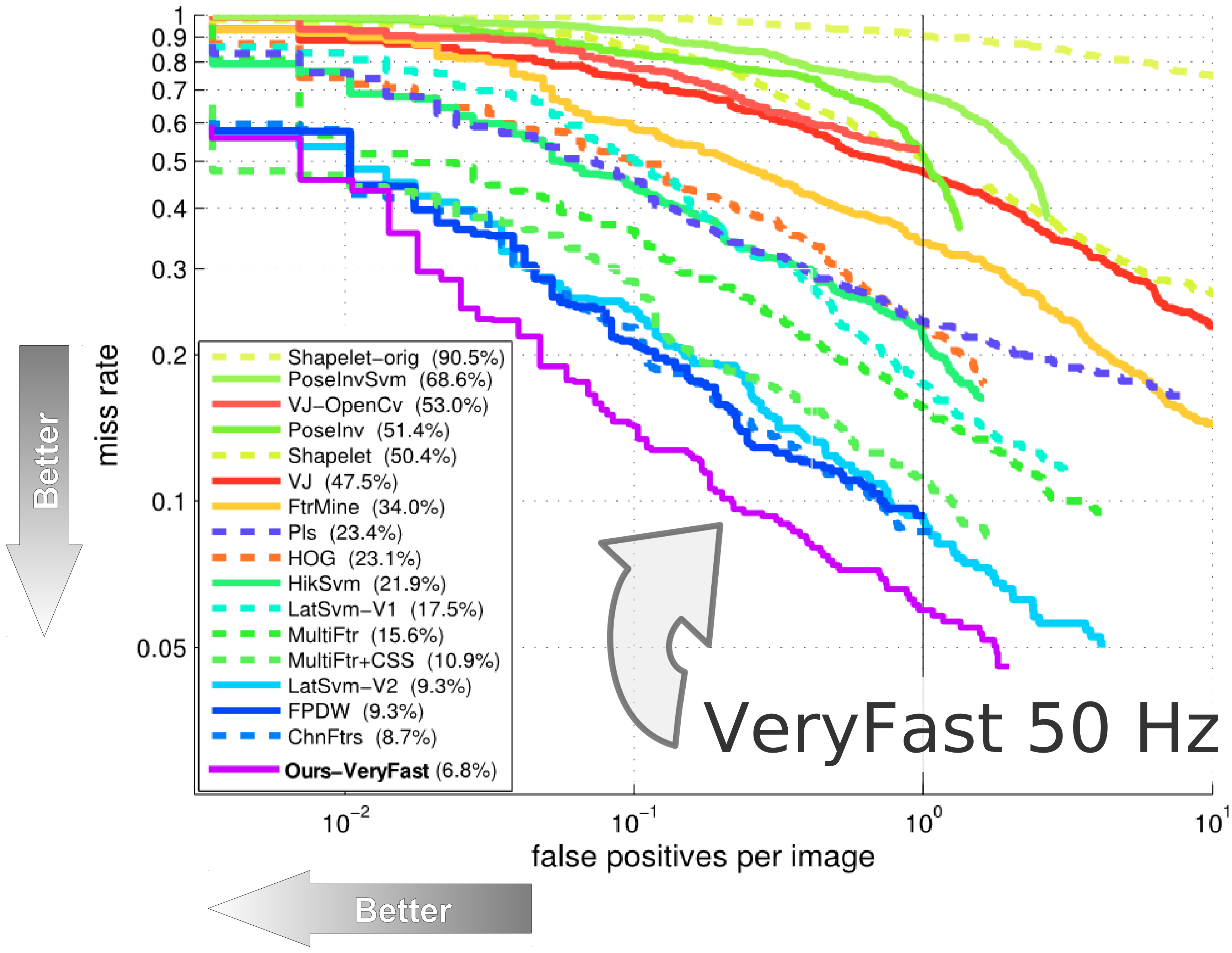
How can we make
things *algorithmically* faster ?

INRIA dataset



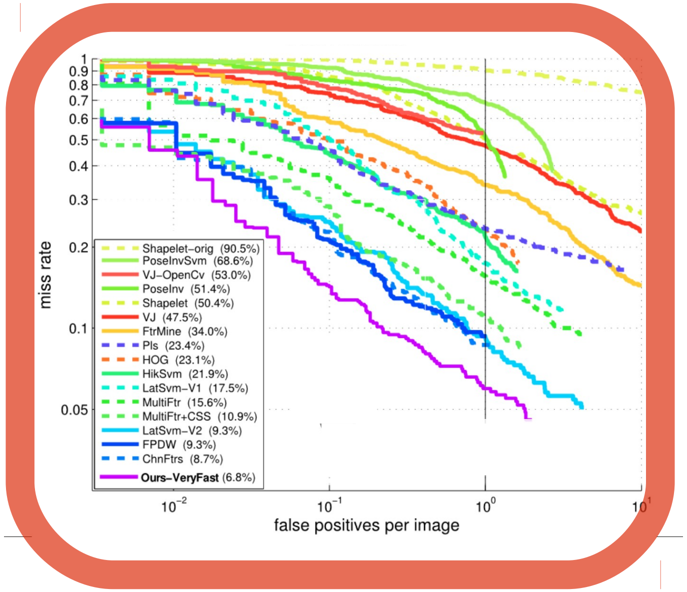
[Dollar et al. 2011]

INRIA dataset

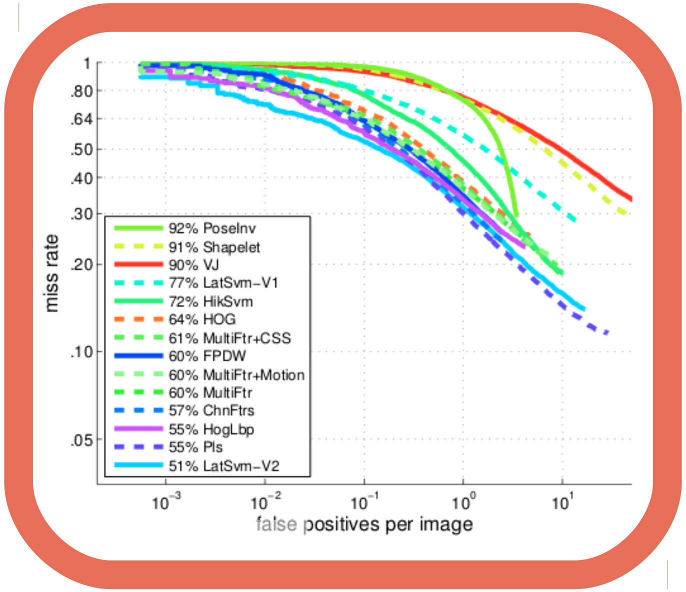


VeryFast 50 Hz

INRIA dataset

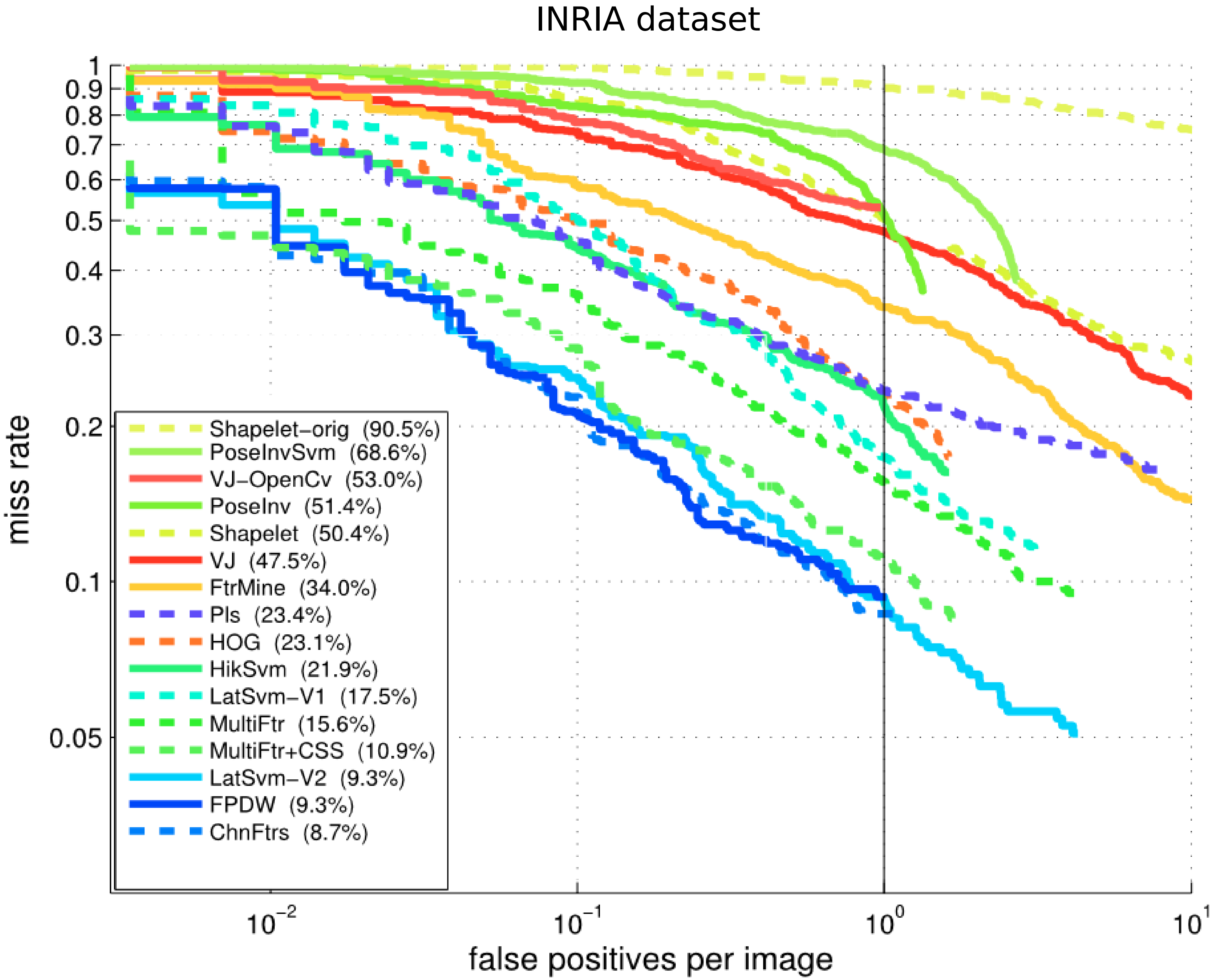


ETH dataset

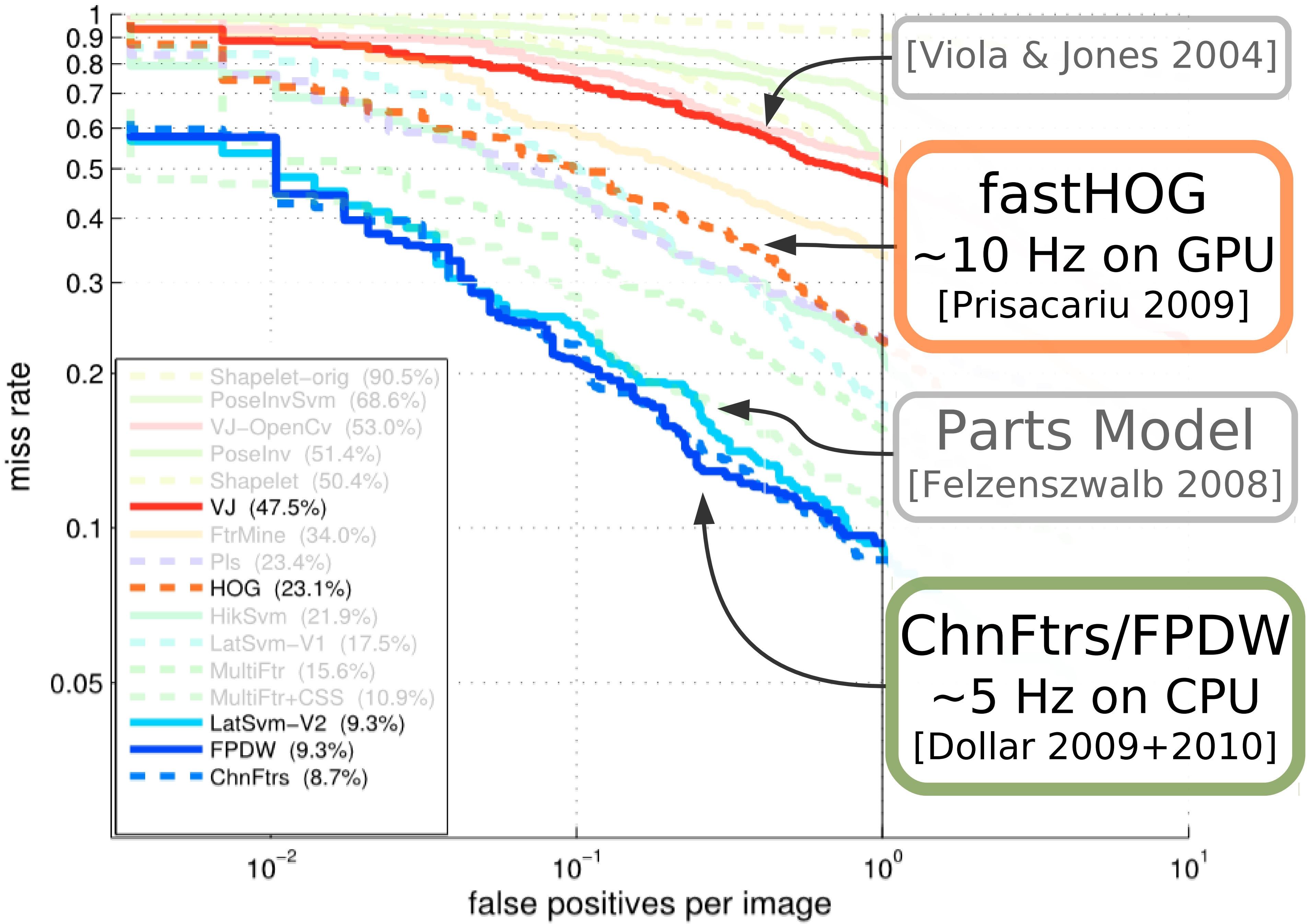


Monocular
50 Hz

Stereo
135 Hz


INRIA dataset
miss rate
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.05
false positives per image
10^{-2}
10^{-1}
10^{0}
10^{1}
Shapelet−orig (90.5%)
PoseInvSvm (68.6%)
VJ−OpenCv (53.0%)
PoseInv (51.4%)
Shapelet (50.4%)
VJ (47.5%)
FtrMine (34.0%)
Pls (23.4%)
HOG (23.1%)
HikSvm (21.9%)
LatSvm−V1 (17.5%)
MultiFtr (15.6%)
MultiFtr+CSS (10.9%)
LatSvm−V2 (9.3%)
FPDW (9.3%)
ChnFtrs (8.7%)

INRIA dataset

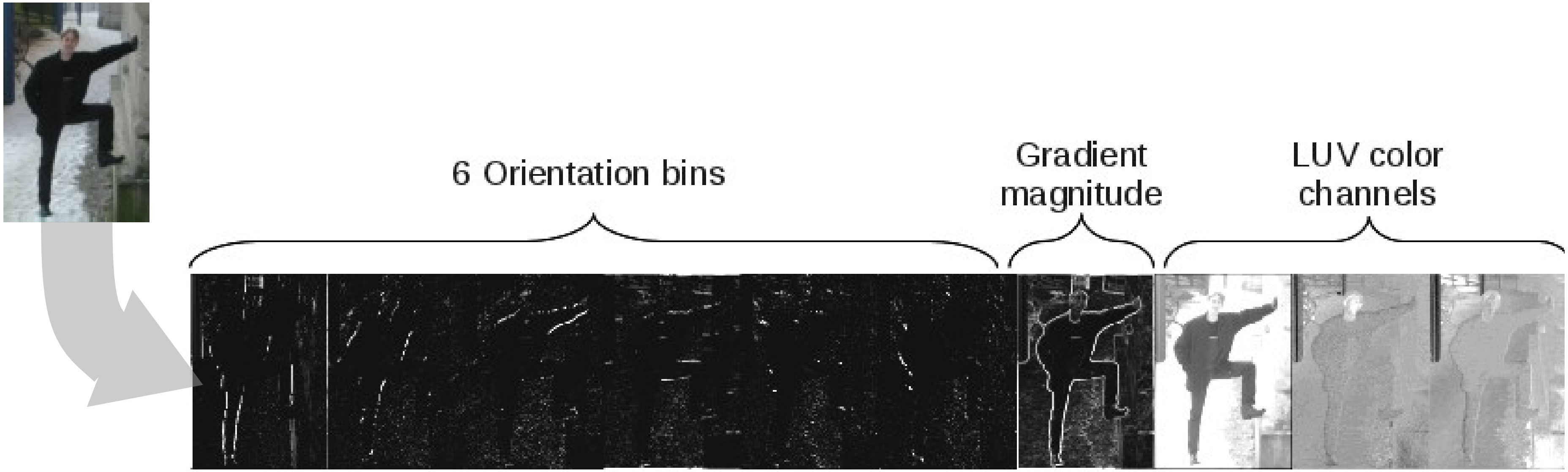


[Viola & Jones 2004]

fastHOG
~10 Hz on GPU
[Prisacariu 2009]

Parts Model
[Felzenszwalb 2008]

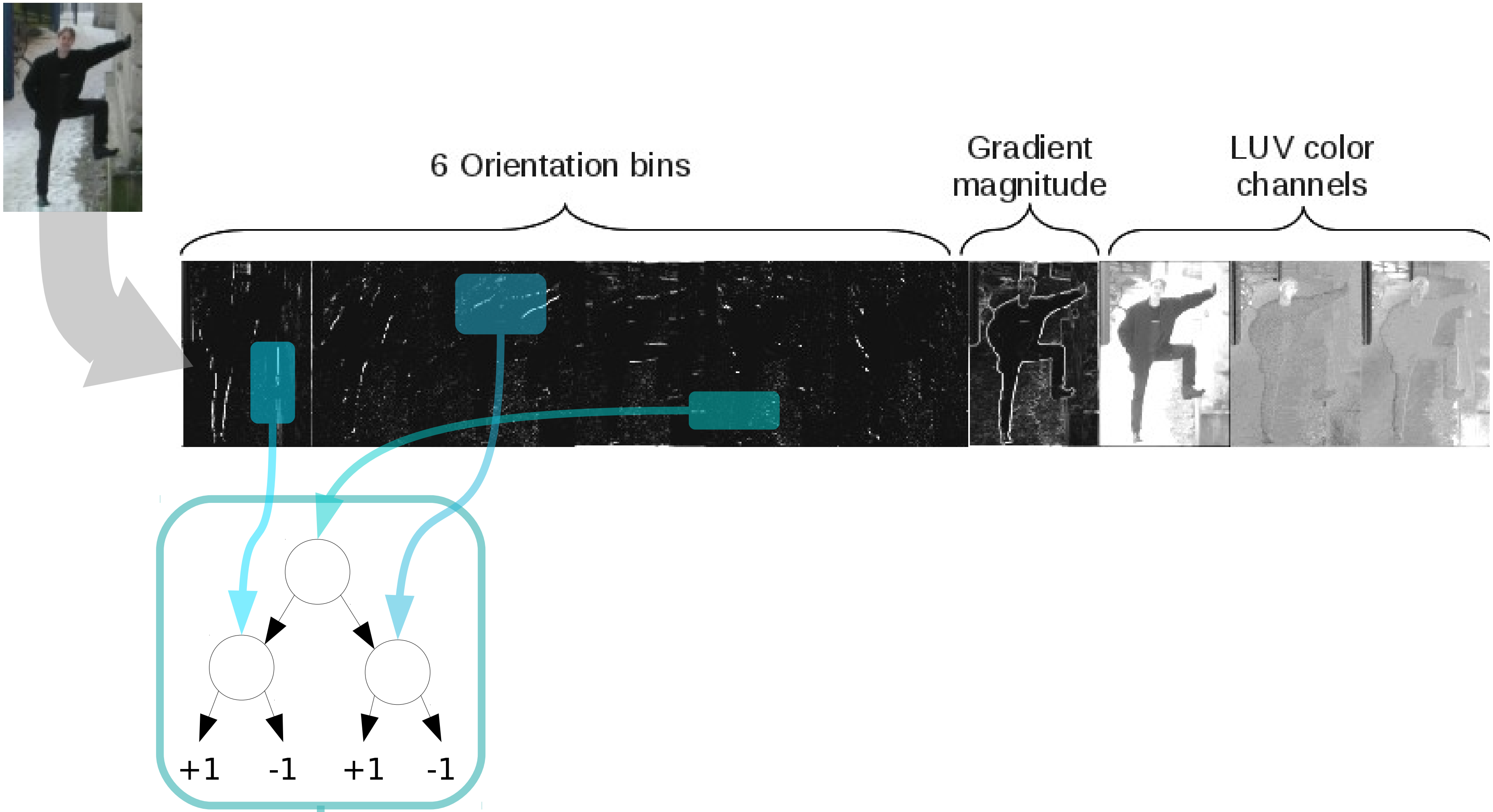
ChnFtrs/FPDW
~5 Hz on CPU
[Dollar 2009+2010]



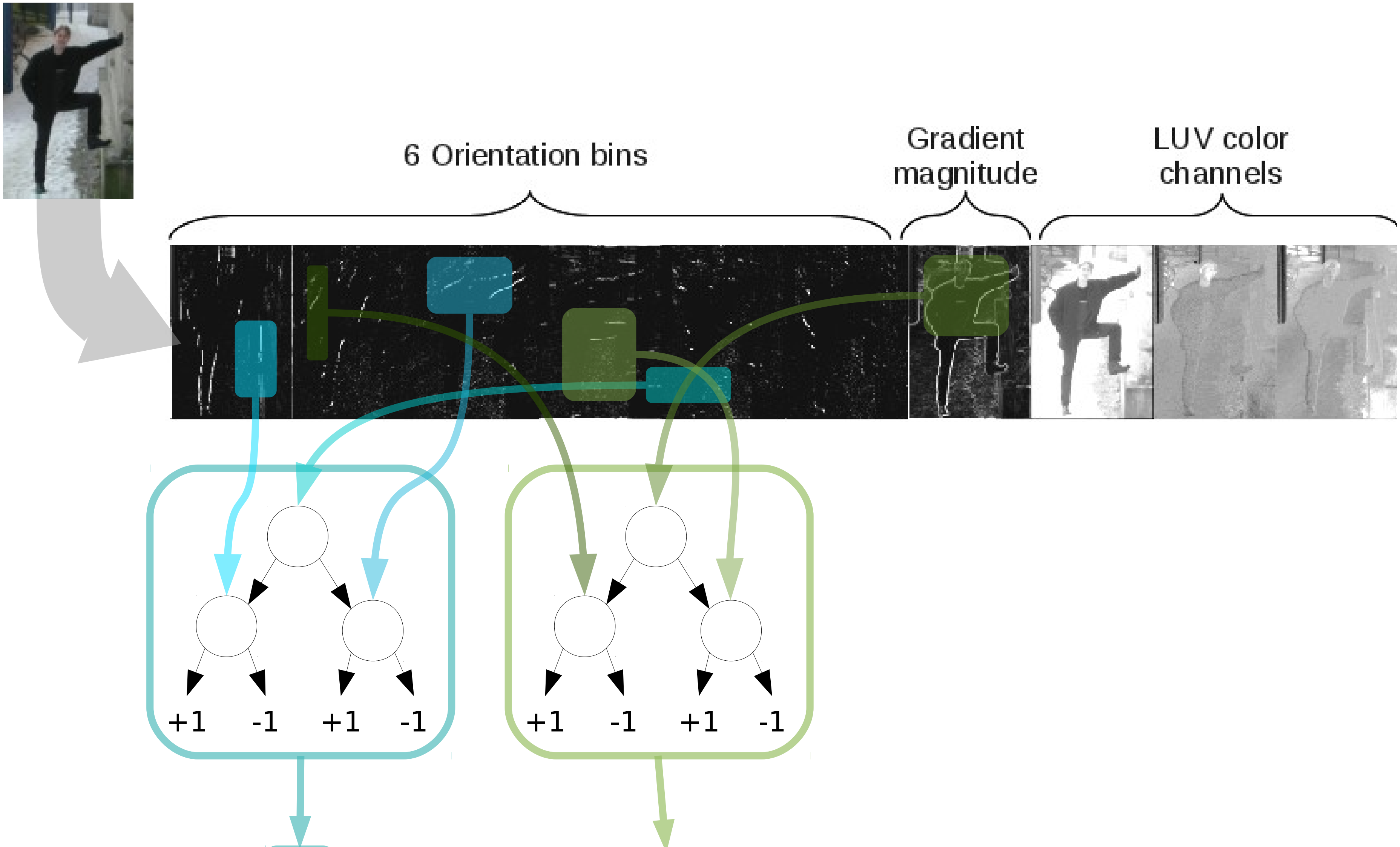
6 Orientation bins

Gradient magnitude

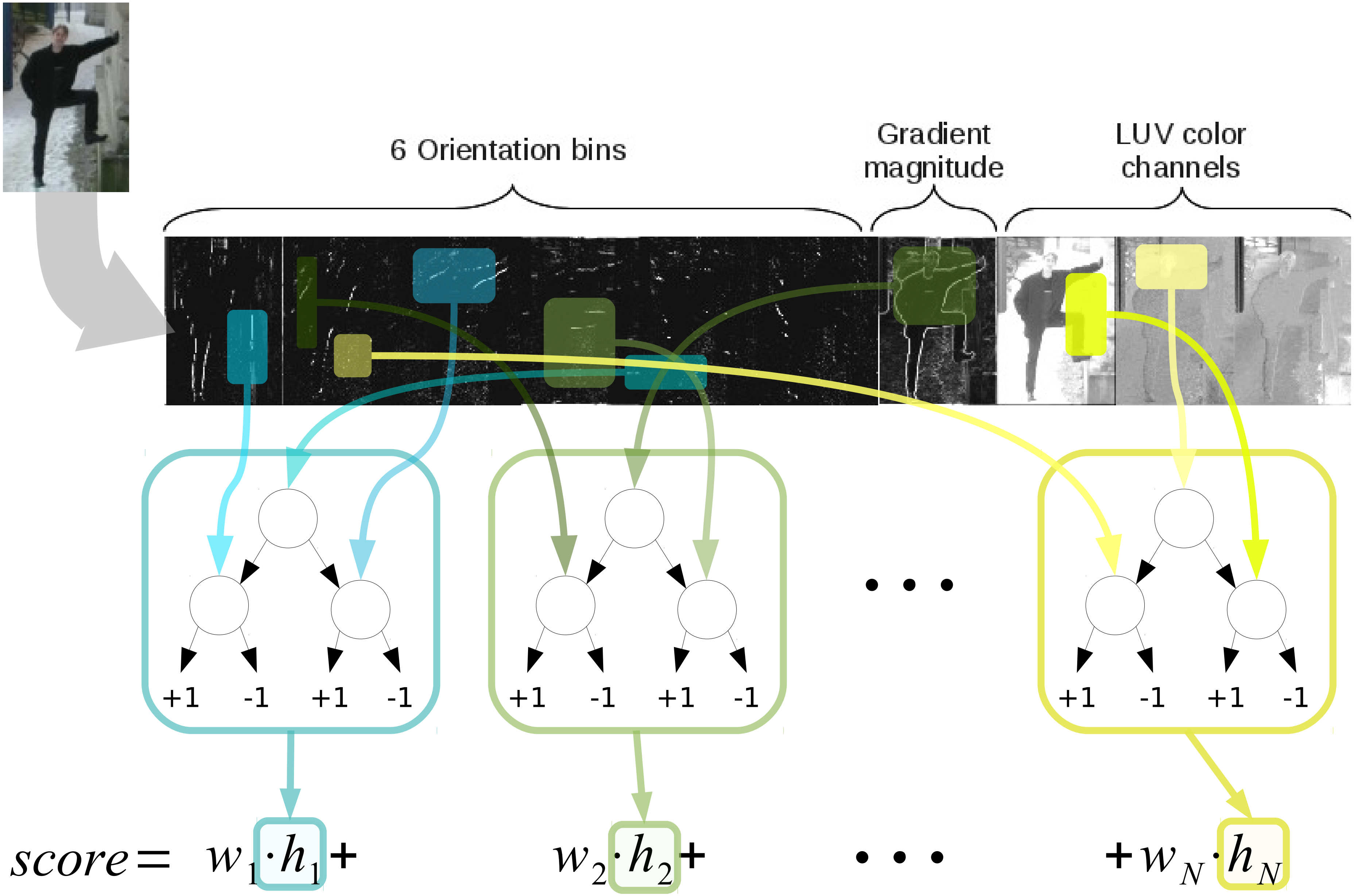
LUV color channels



$$score = w_1 \cdot \boxed{h_1} +$$



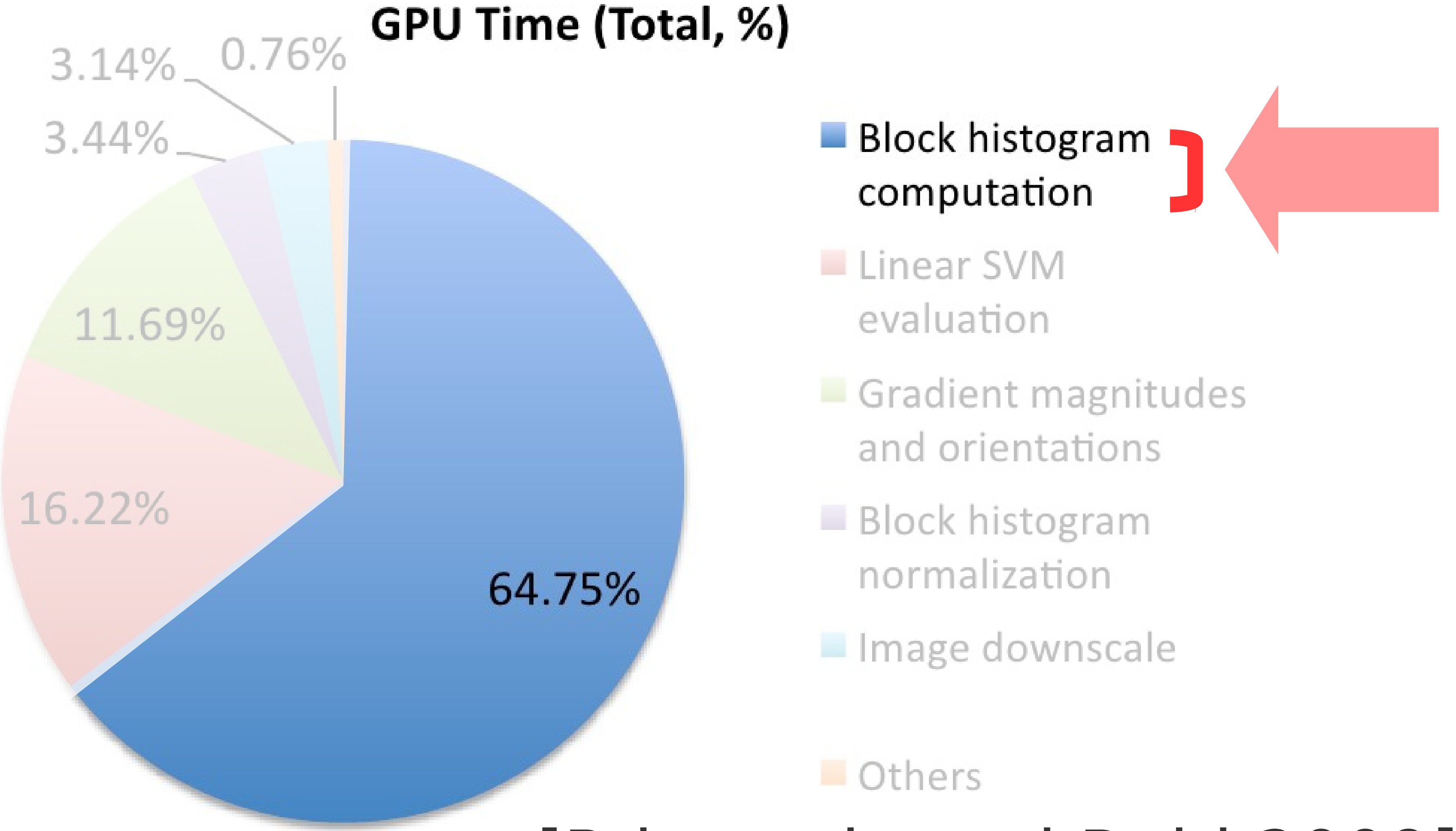
$$score = w_1 \cdot \boxed{h_1} + \quad w_2 \cdot \boxed{h_2} +$$



$$score = w_1 \cdot \boxed{h_1} + \; w_2 \cdot \boxed{h_2} + \; \cdots \; + w_N \cdot \boxed{h_N}$$

[ChnFtrs, Dollar et al. 2009] (~4 Hz on GPU)

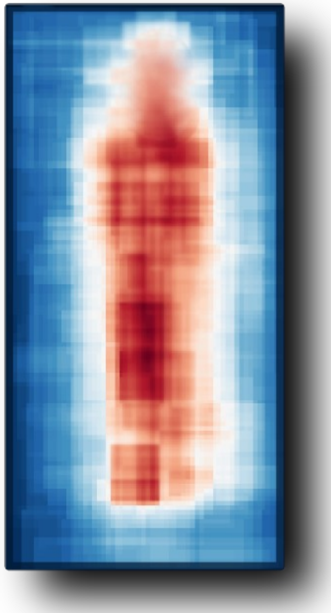
What slows down fastHOG ?

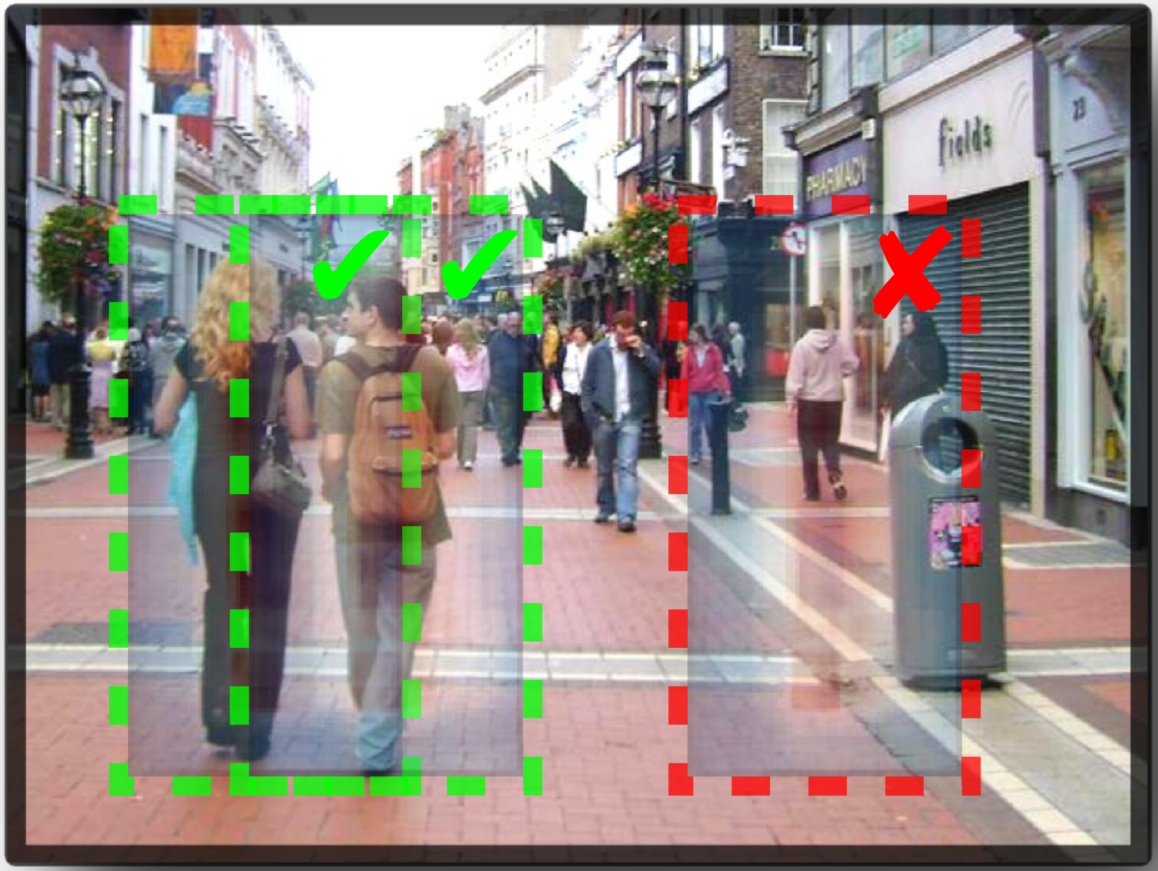


[Prisacariu and Reid 2009]

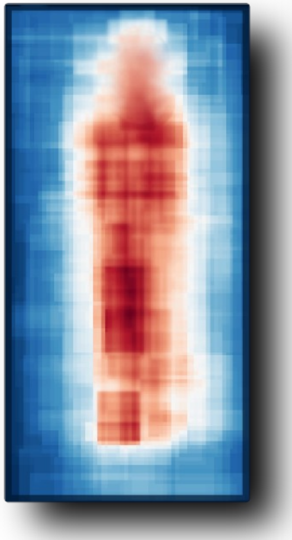
How to make *features computation* faster ?

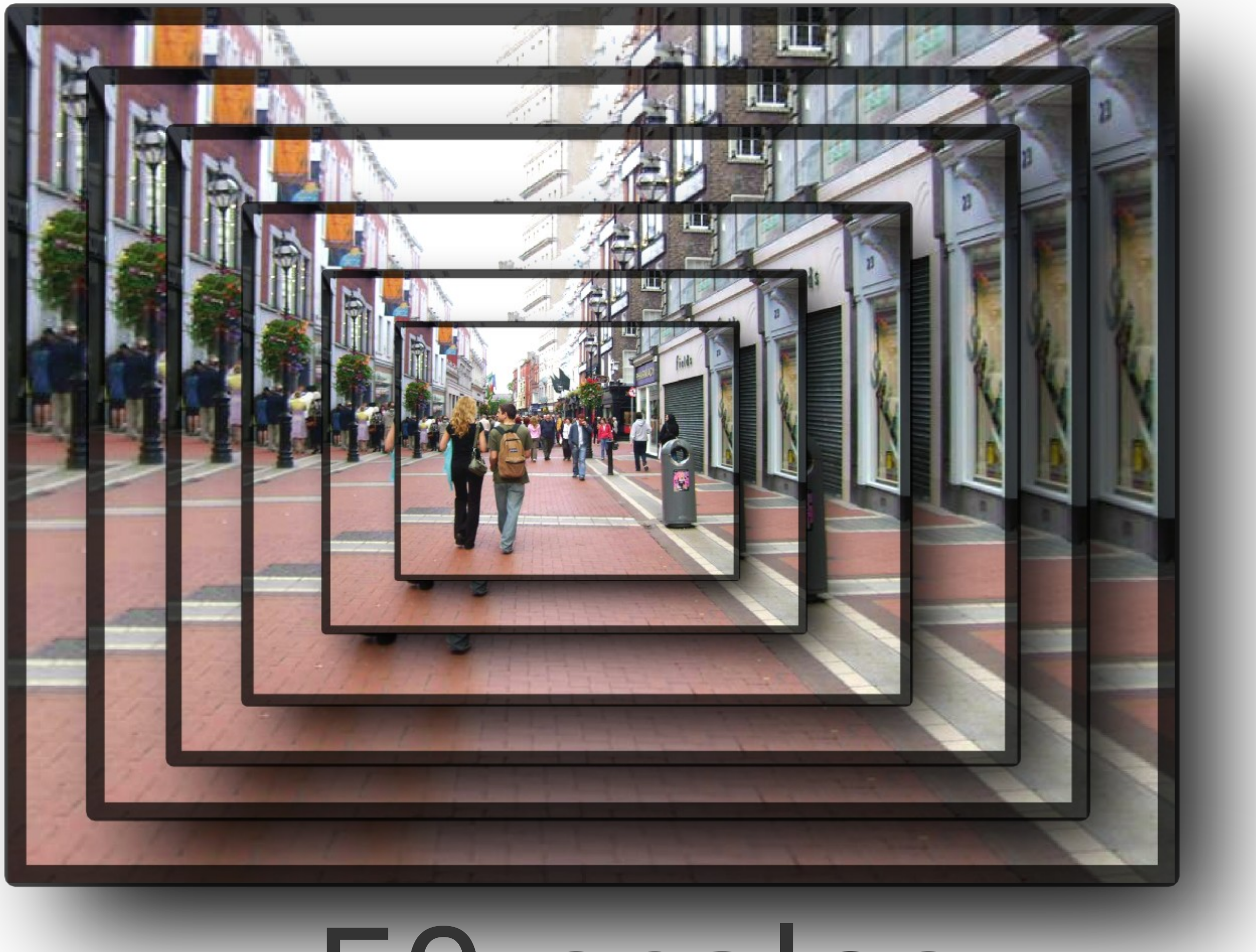
One template cannot detect at multiple scales





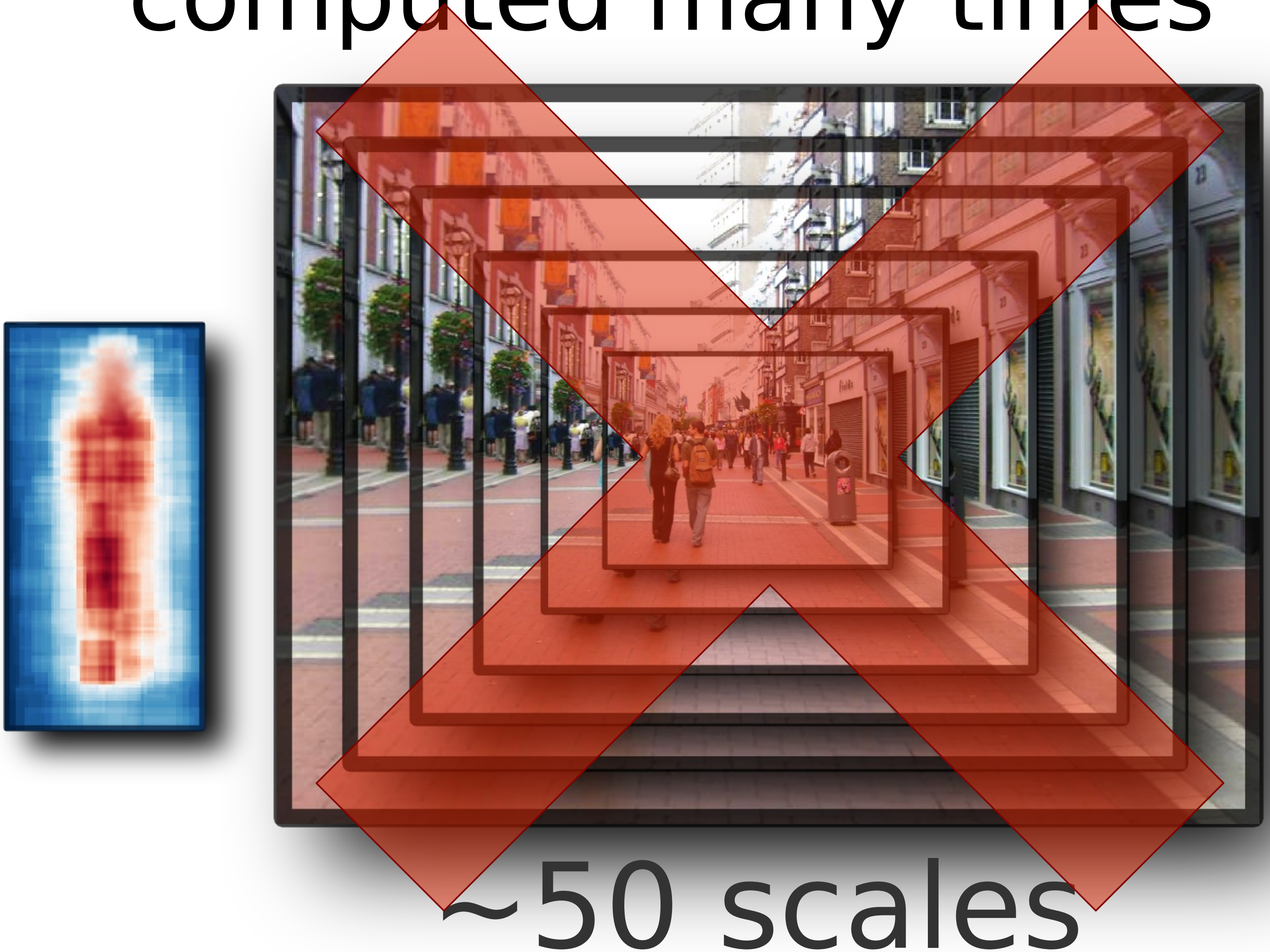
Traditionally, features are computed many times



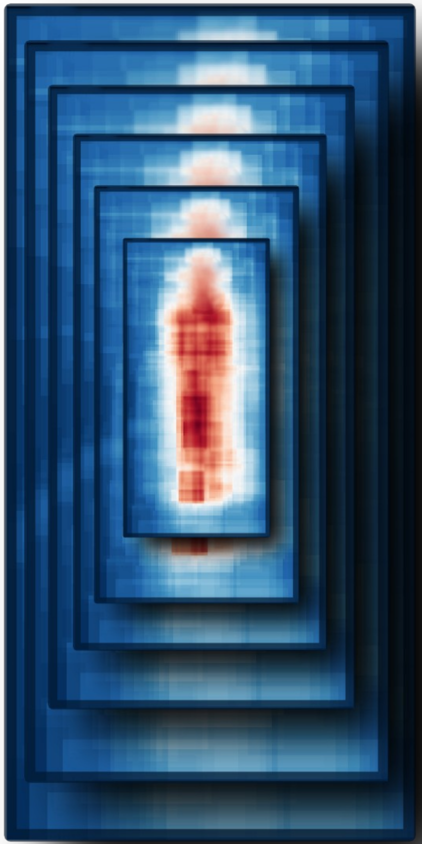


~50 scales

Traditionally, features are computed many times



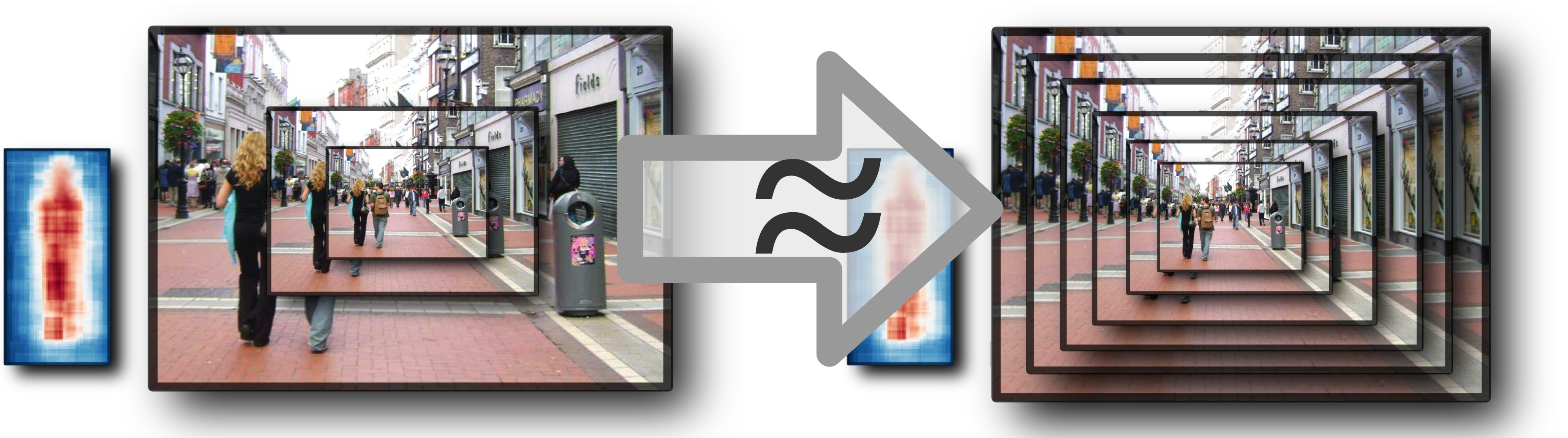
Training one model per scale is too expensive



~50 scales

Can we avoid resizing
the input image many times ?

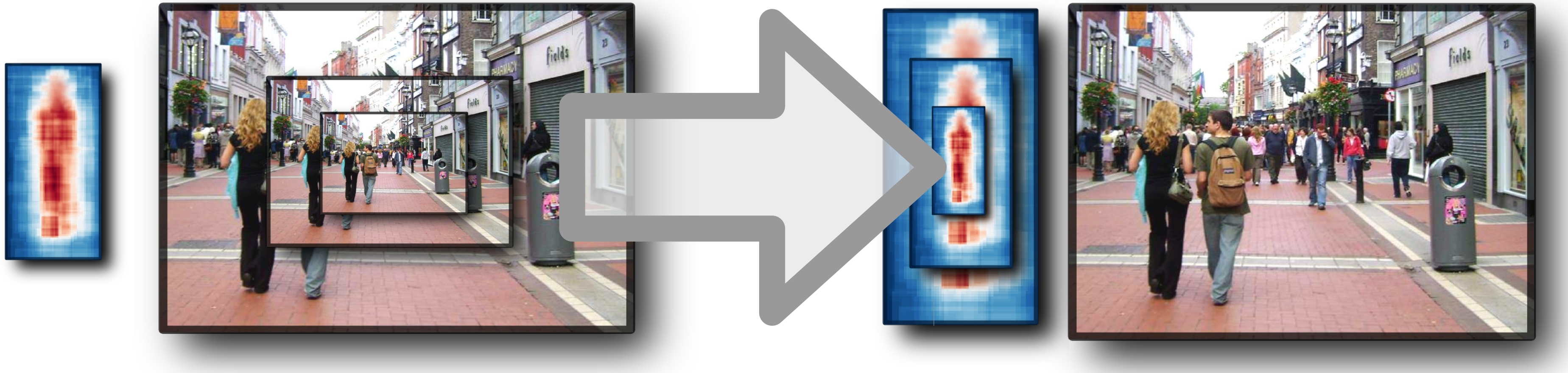
Features can be approximated across scales



~5 scales ~50 scales

[Dollar et al. 2010]

We transfer test time computation to training time

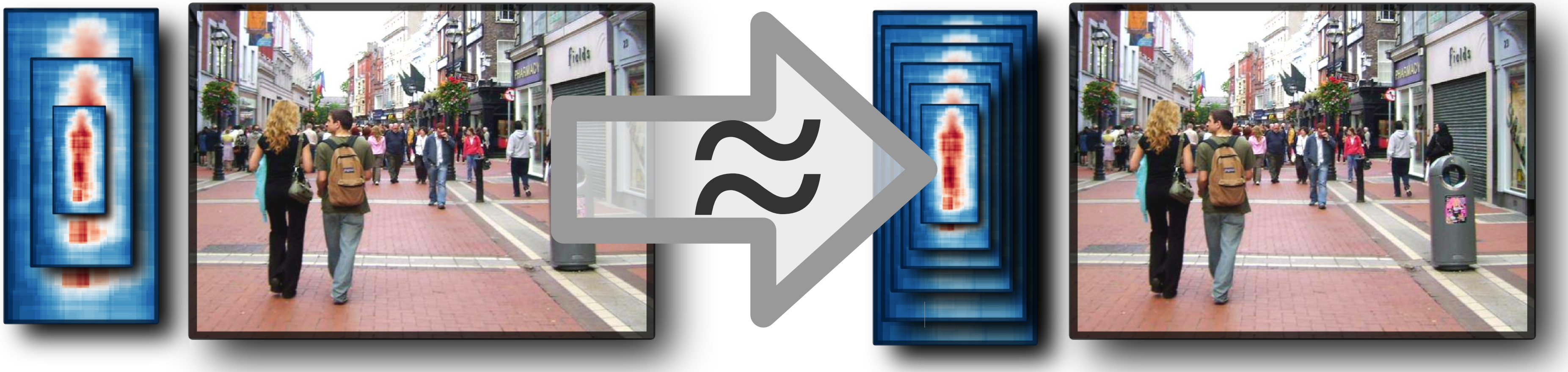


1 model,
5 image scales

5 models,
1 image scale

(3x reduction in features computation)

At runtime, we use as many models as scales



5 models,
1 image scale

50 models,
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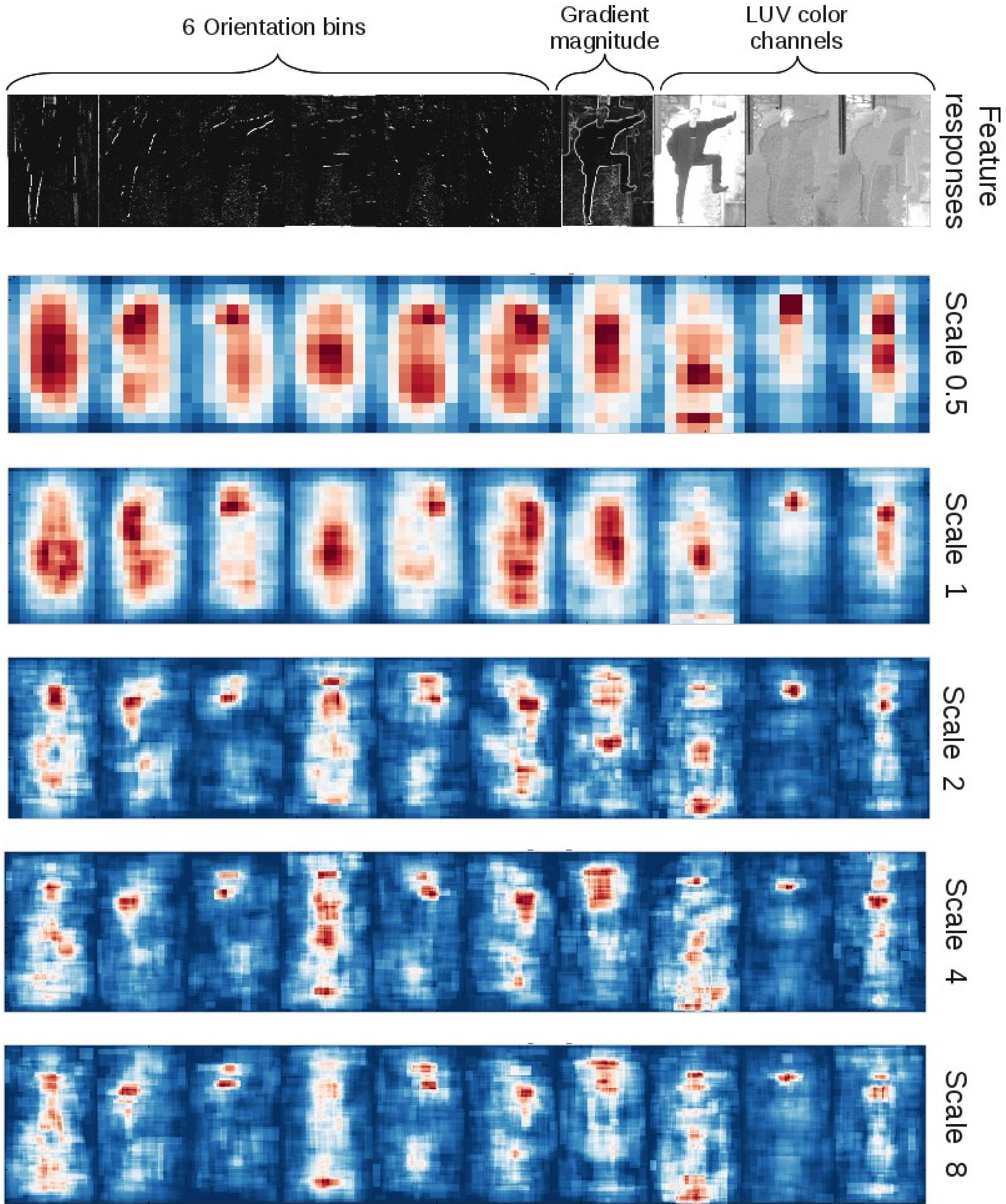
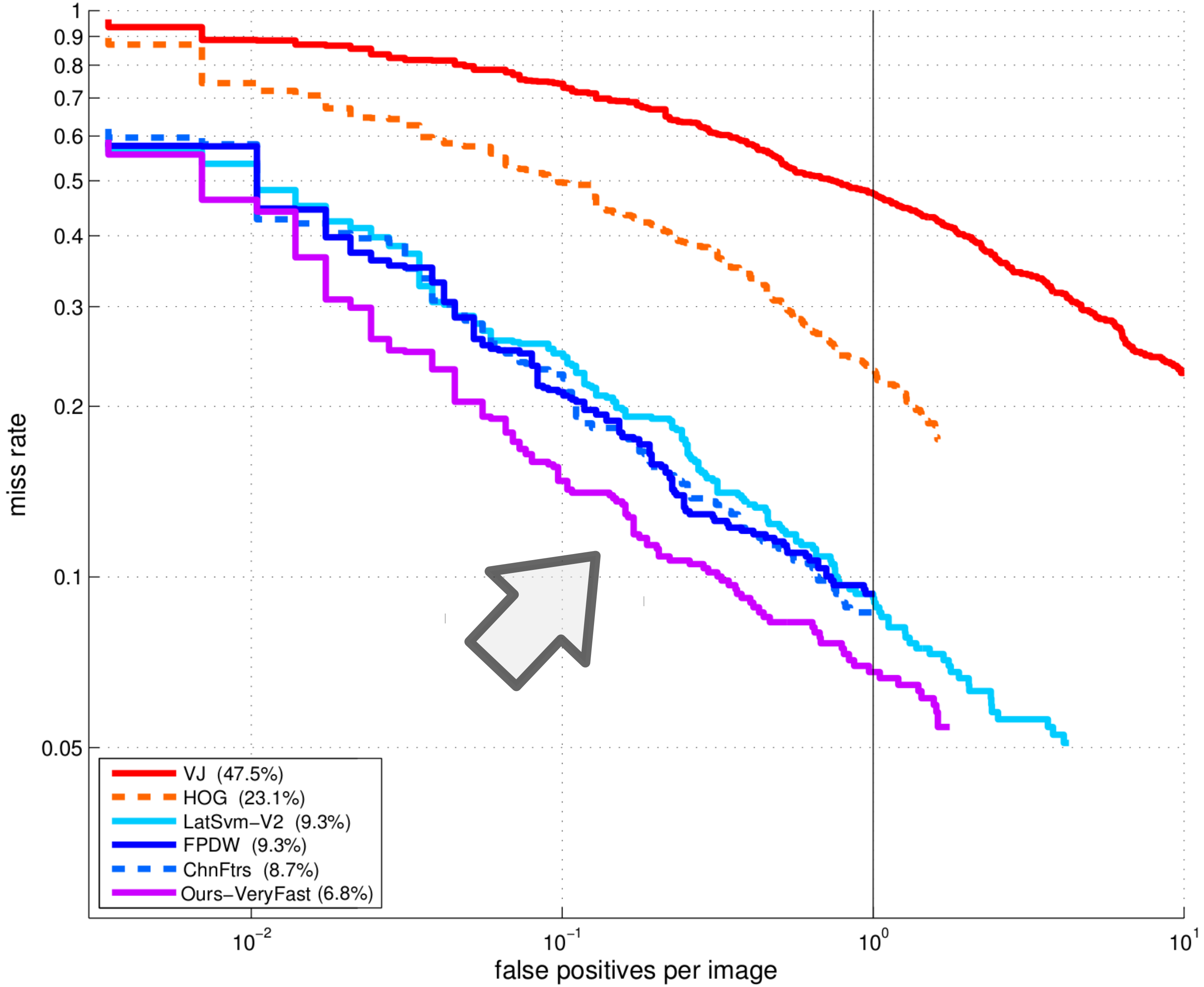

6 Orientation bins
Gradient magnitude
LUV color channels
Feature responses
Scale 0.5
Scale 1
Scale 2
Scale 4
Scale 8

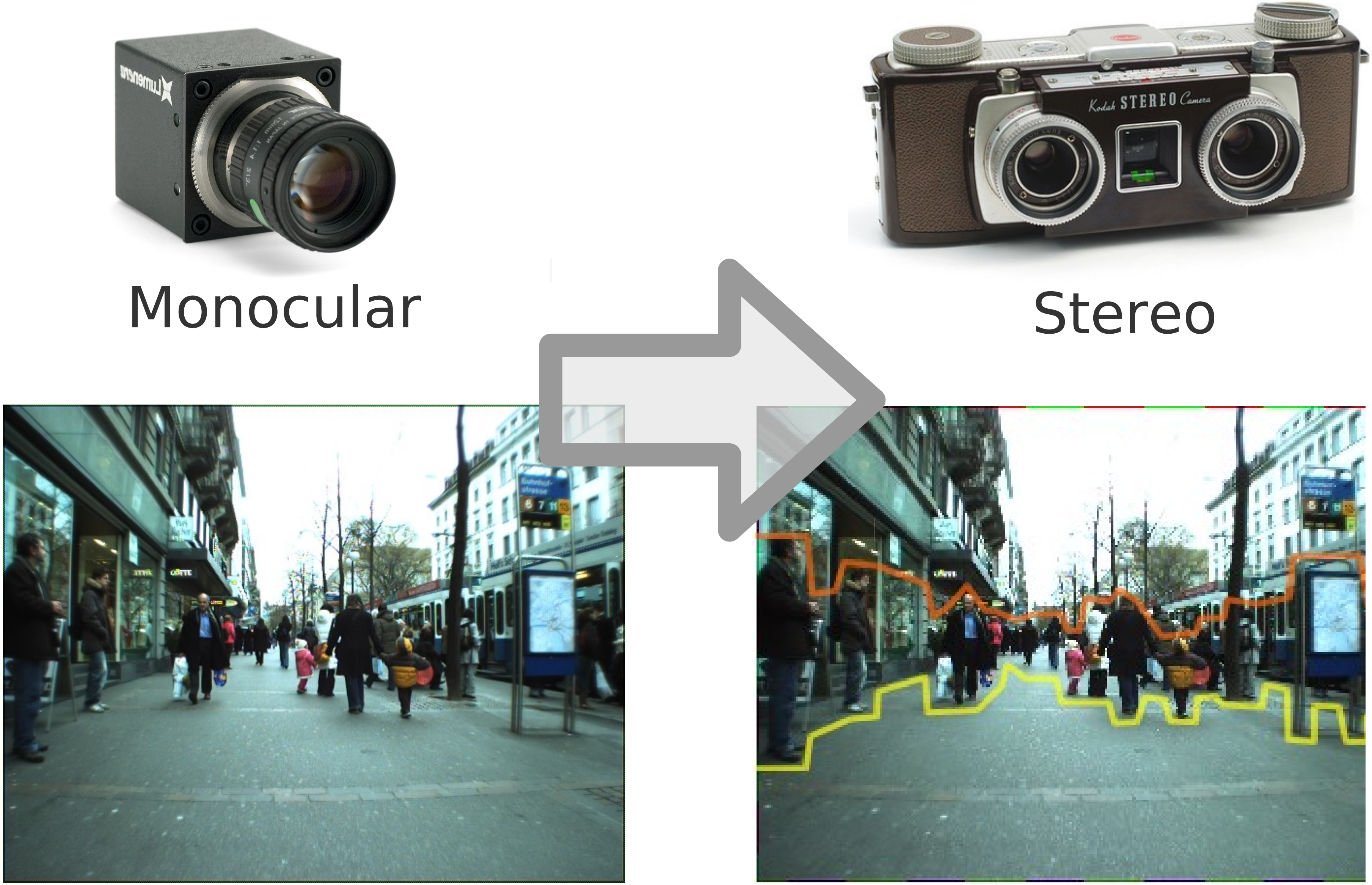
Detecting without resizing provides quality



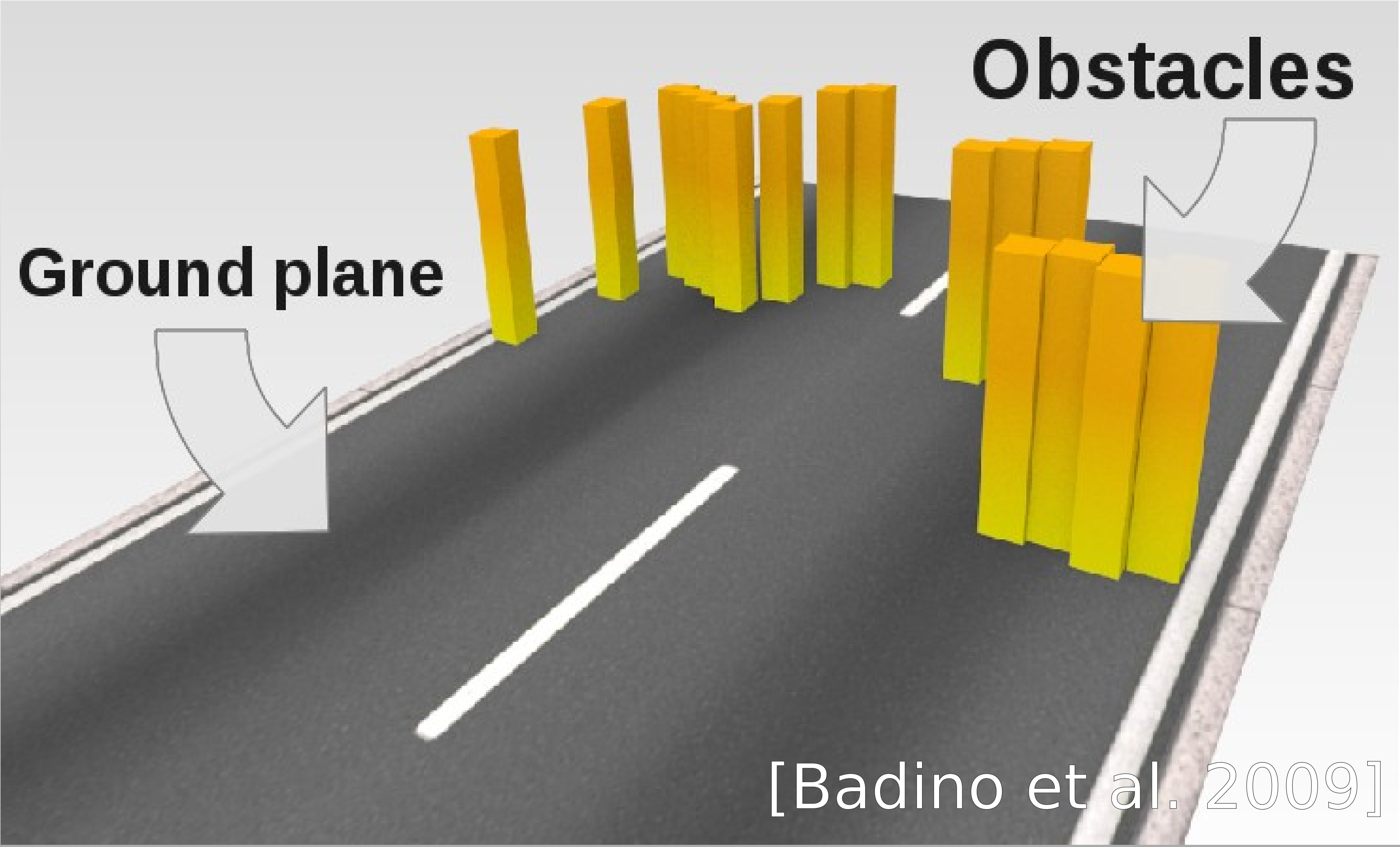
Detecting without resizing provides speed

- ~3x less time on features computation
- Avoids alternating between features and detection scores computation (relevant in practice)
- We reach **50 Hz** on GPU, 640x480 pixels x 55 scales

We want to use scene geometry to guide the detections

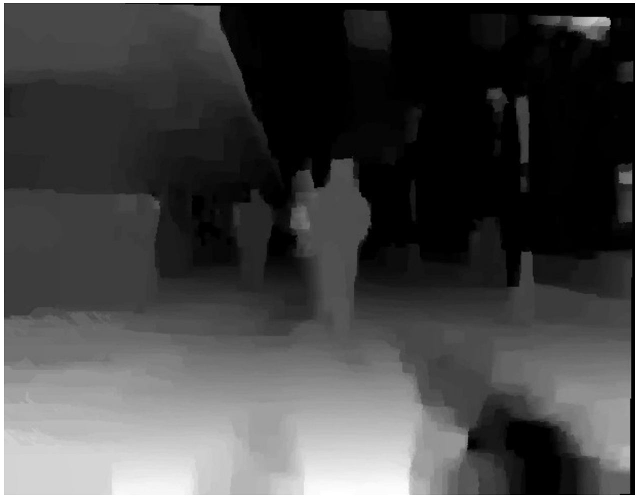


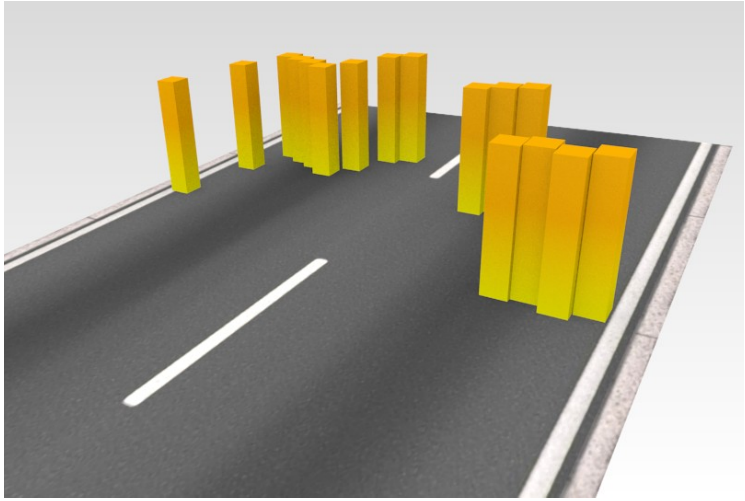
Stixel world



[Badino et al. 2009]

Depth maps are slow to compute

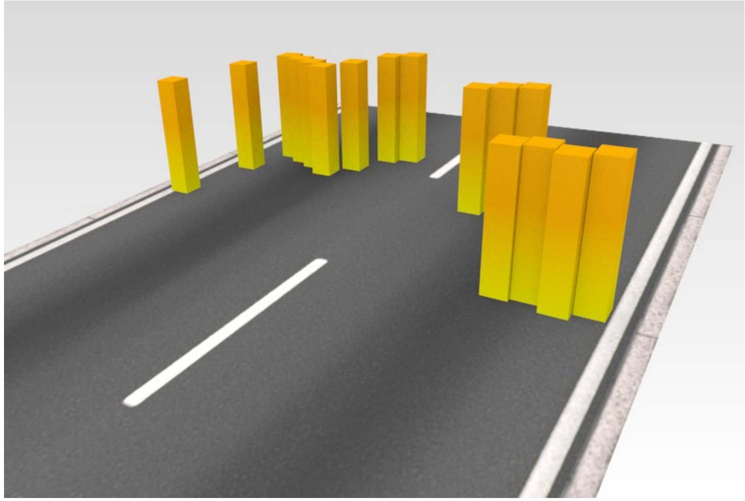




<50 Hz on CPU

Stixel world without depth map

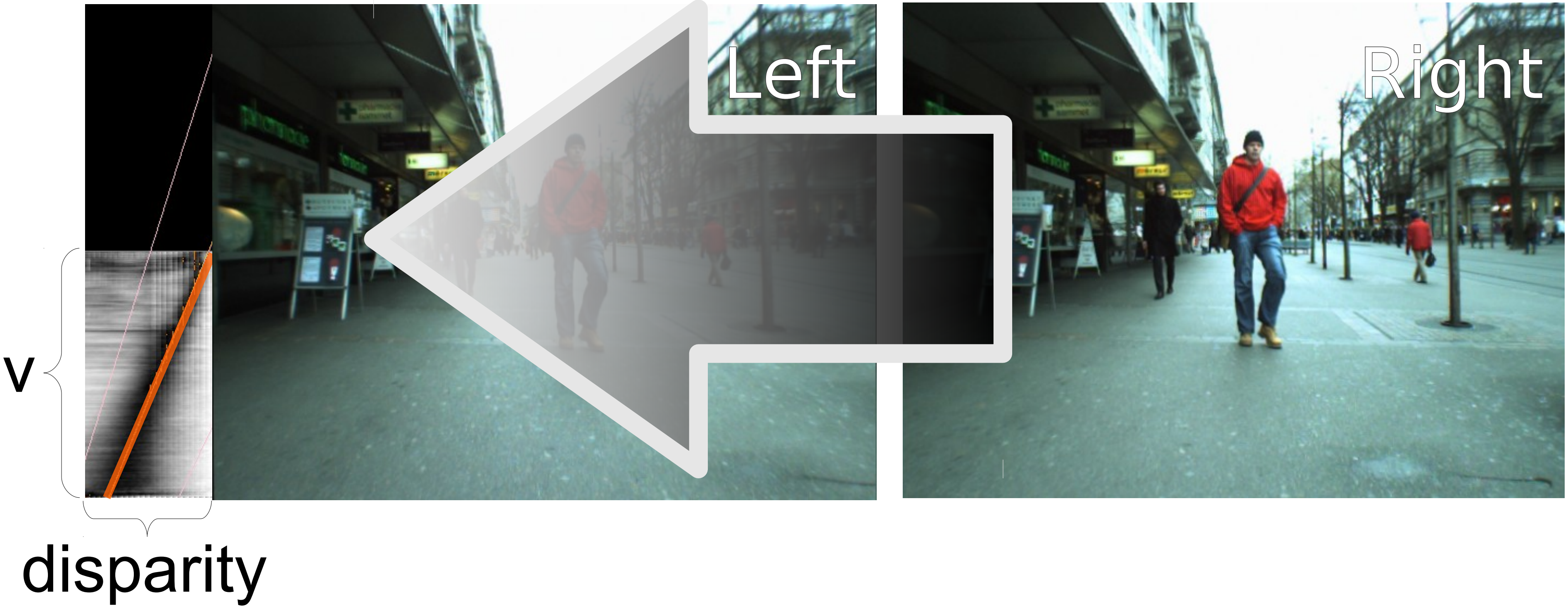
135 Hz on CPU



[Benenson et al. 2011]

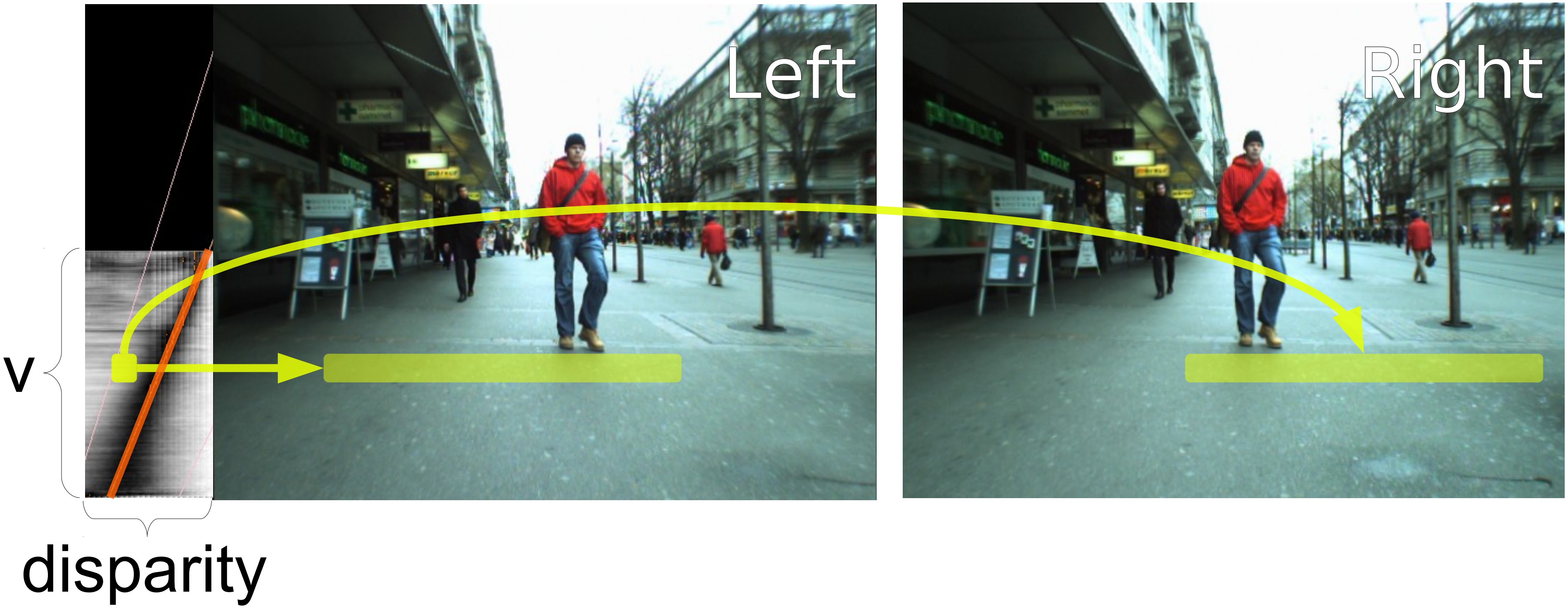
Stixel world without depth map

Stixel world without depth map



1) Ground plane estimation

Stixel world without depth map



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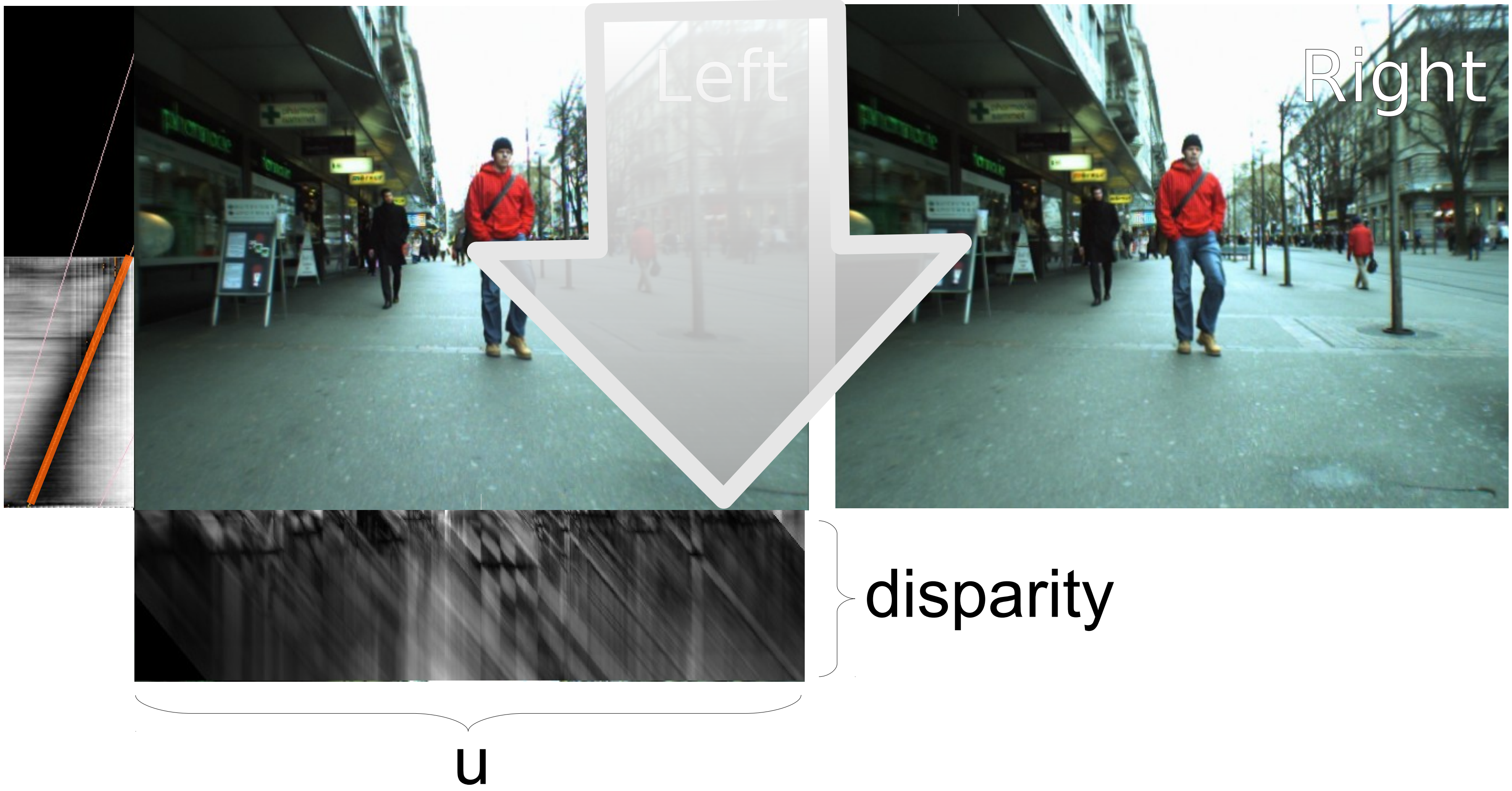
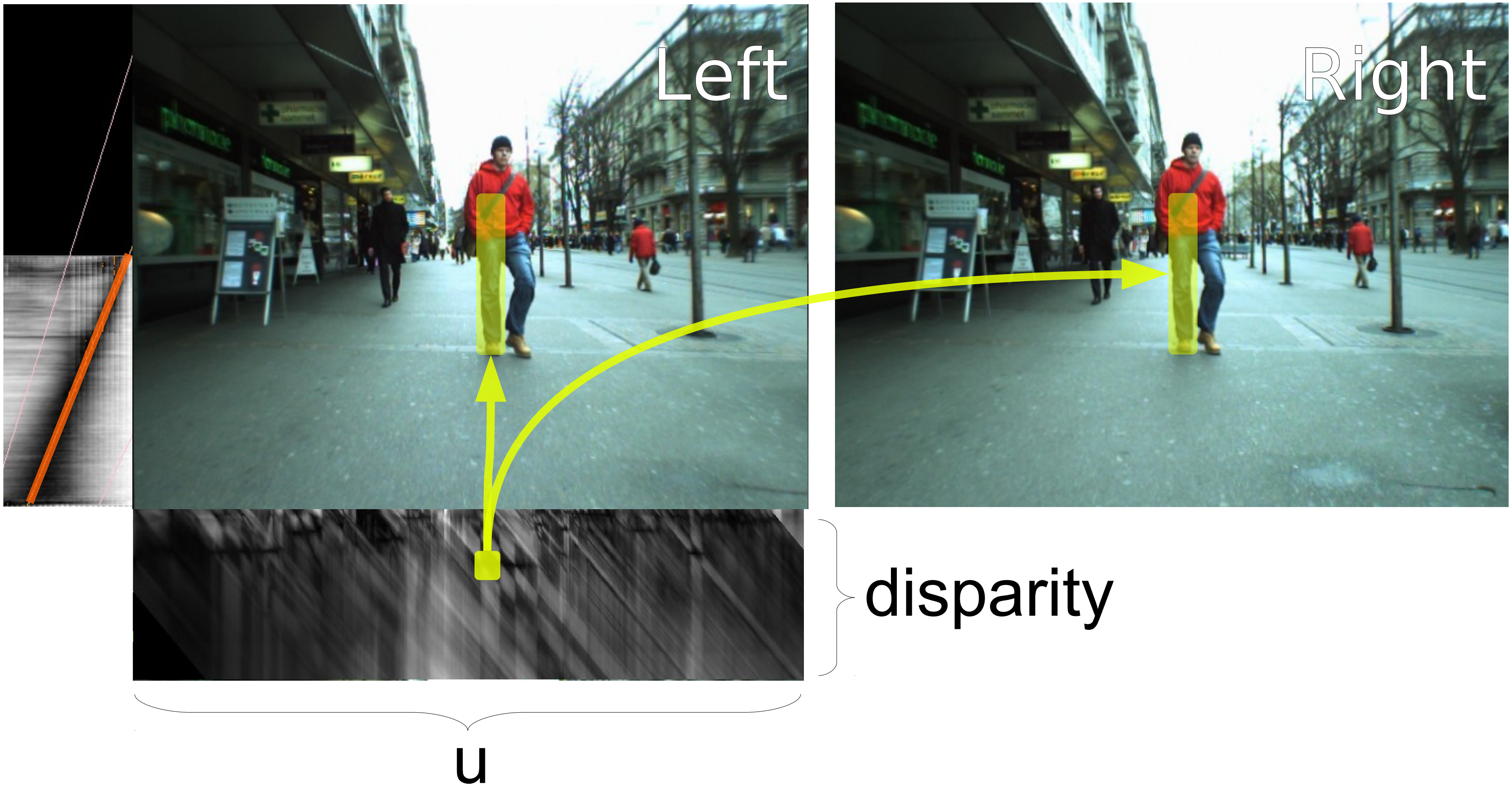
Stixel world without depth map



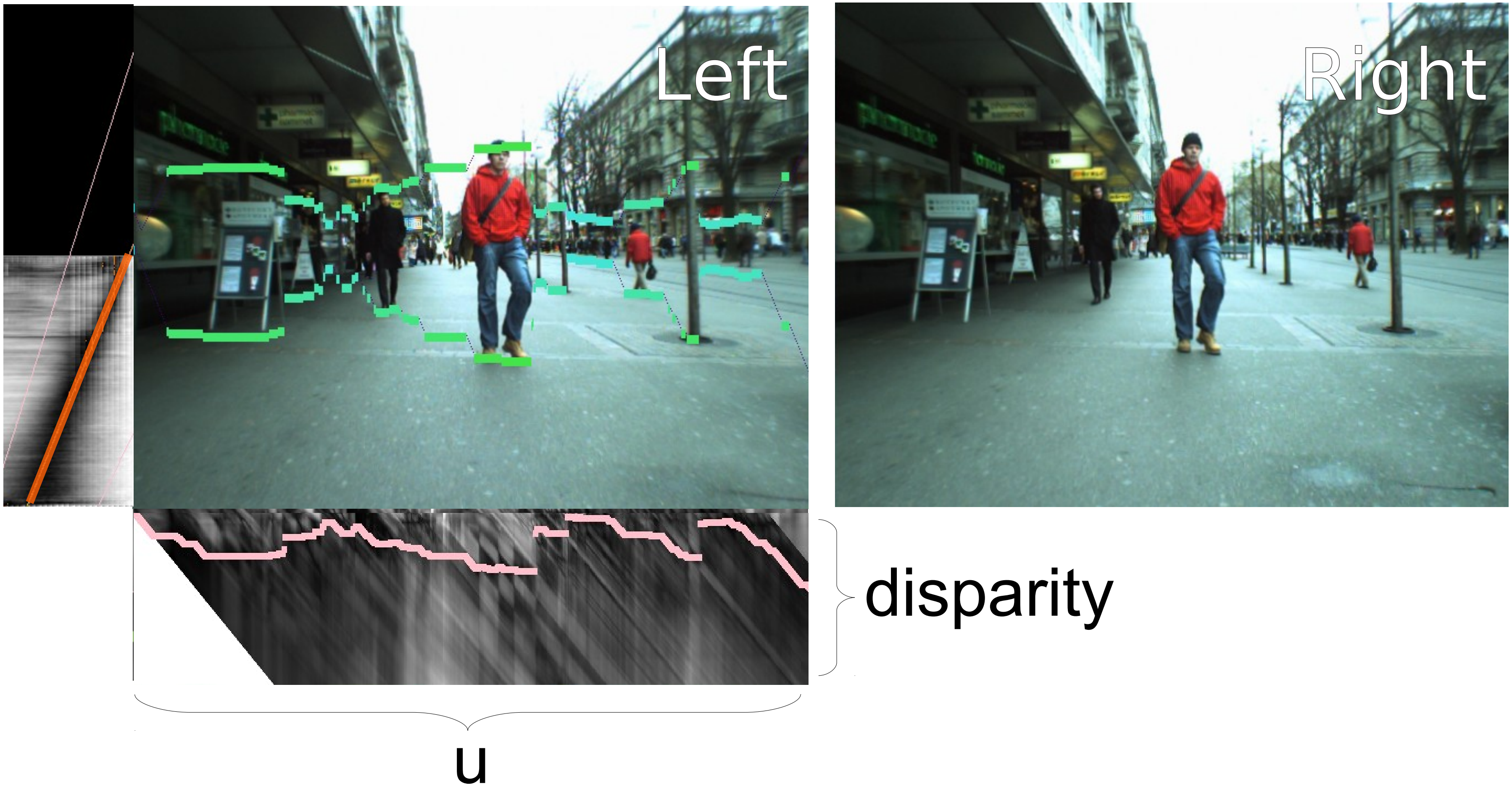
2) Stixel distance estimation

Stixel world without depth map



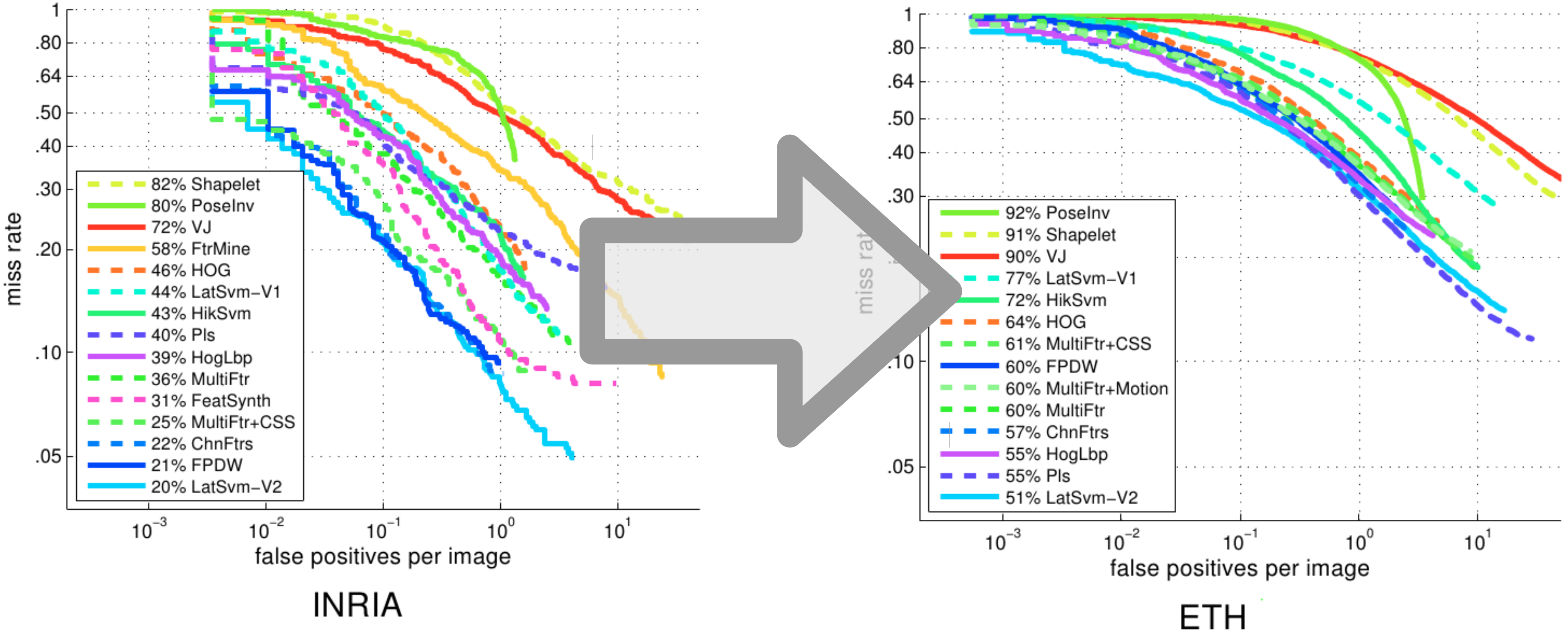
2) Stixel distance estimation

Stixel world without depth map



2) Stixel distance estimation @ 135 Hz CPU

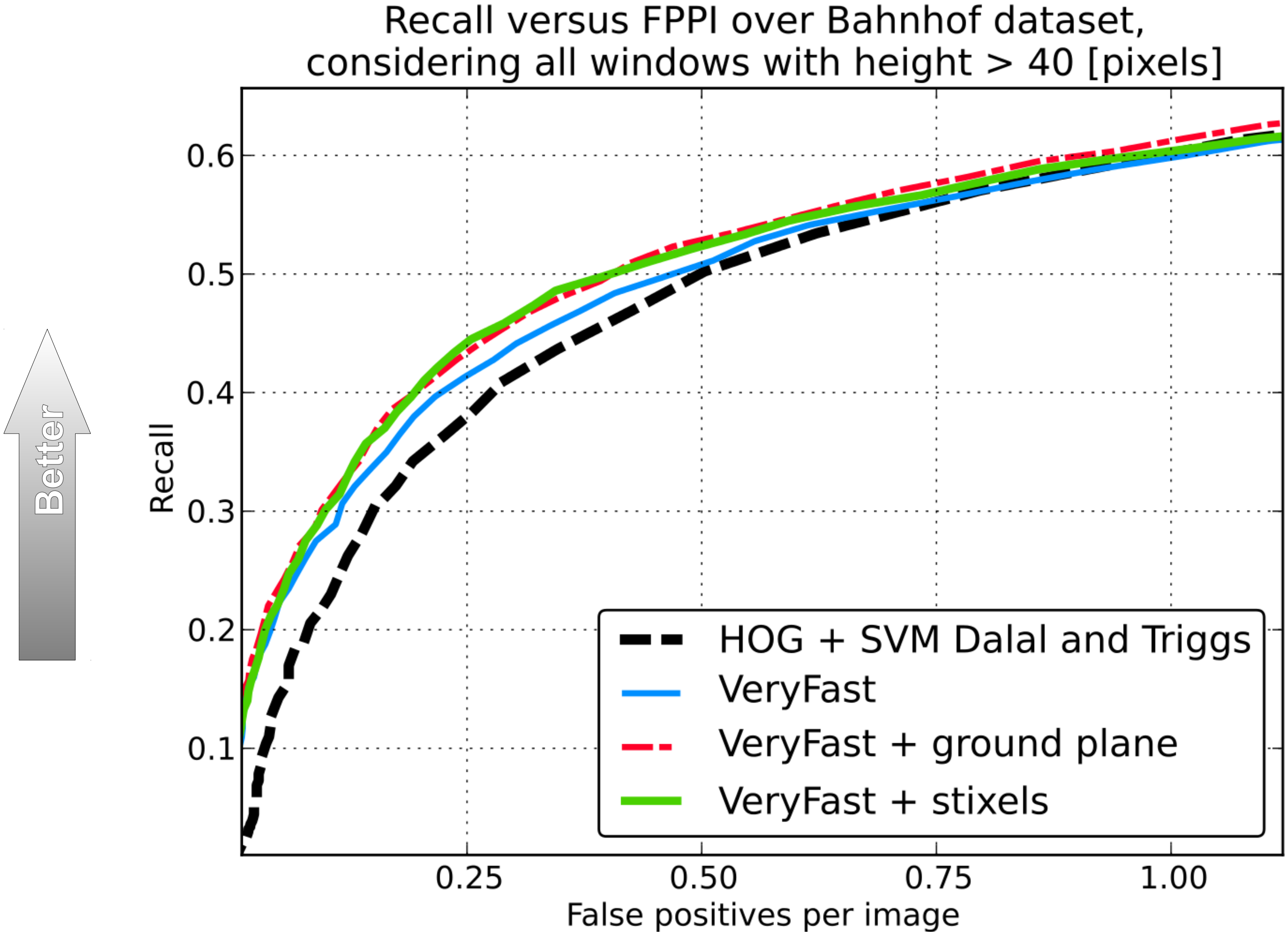
ETH's dataset results have less variance than INRIA's



Monocular

Stereo

Using stixels provides speed without quality loss



Detecting using stixels provides speed

- No geometry:
  - 640x480 pixels x 55 scales => 50 Hz on desktop
- Ground plane:
  - 640x60 pixels x 55 scales => 100 Hz on desktop (8x reduction in search space)
- Stixels:
  - 640x60 pixels x 10 scales => **135 Hz** on desktop (150 Hz GPU side, 135 Hz CPU side)
  - 44x reduction in search space
  - We reach *80 Hz on laptop*

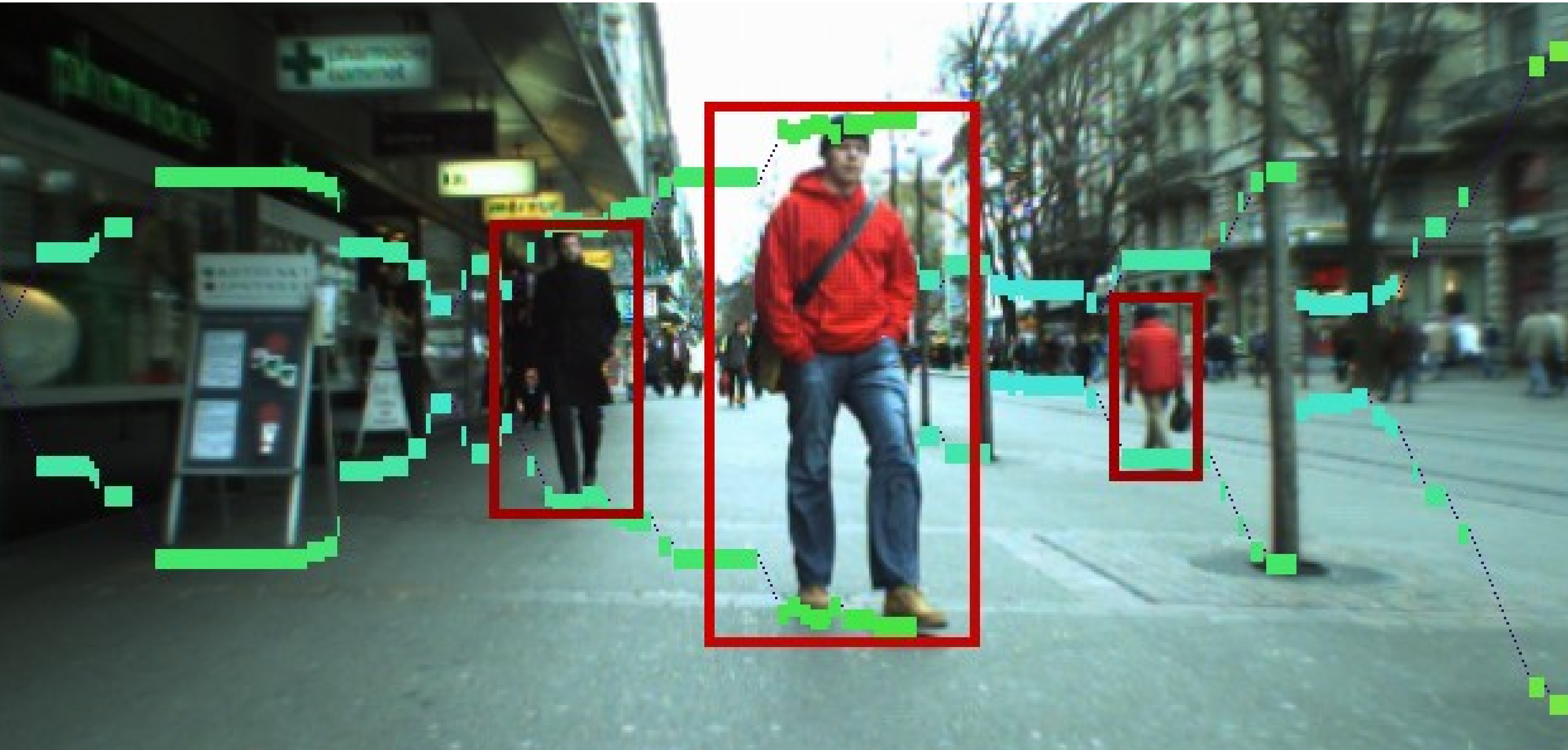
Win-win detector

- **High**est known **quality** for a single part detector
  (over the INRIA dataset, at camera ready time)

- 50 Hz in monocular mode,
  135 Hz in **stereo mode**, *80 Hz on a laptop*.

- 5x faster and 3x lower missrate
  than previous state-of-the-art, fastHOG.

No resizing + stixels
==
faster and better detections



Future work

- Transforming classifier seems useful:
  - Extension for different occlusions (submitted)
  - Extension for different point of views ?

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  - Extension for different occlusions (submitted)
  - Extension for different point of views ?

- There is room for speed and quality improvements
  - (Original implementation was crude,
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Future work

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  - Extension for different occlusions (submitted)
  - Extension for different point of views ?

- There is room for speed and quality improvements
  - (Original implementation was crude,
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- Building a part pased model
  on top of our VeryFast detector ?

?

Rodrigo Benenson

http://rodrigob.github.com

Source code release on August 1st

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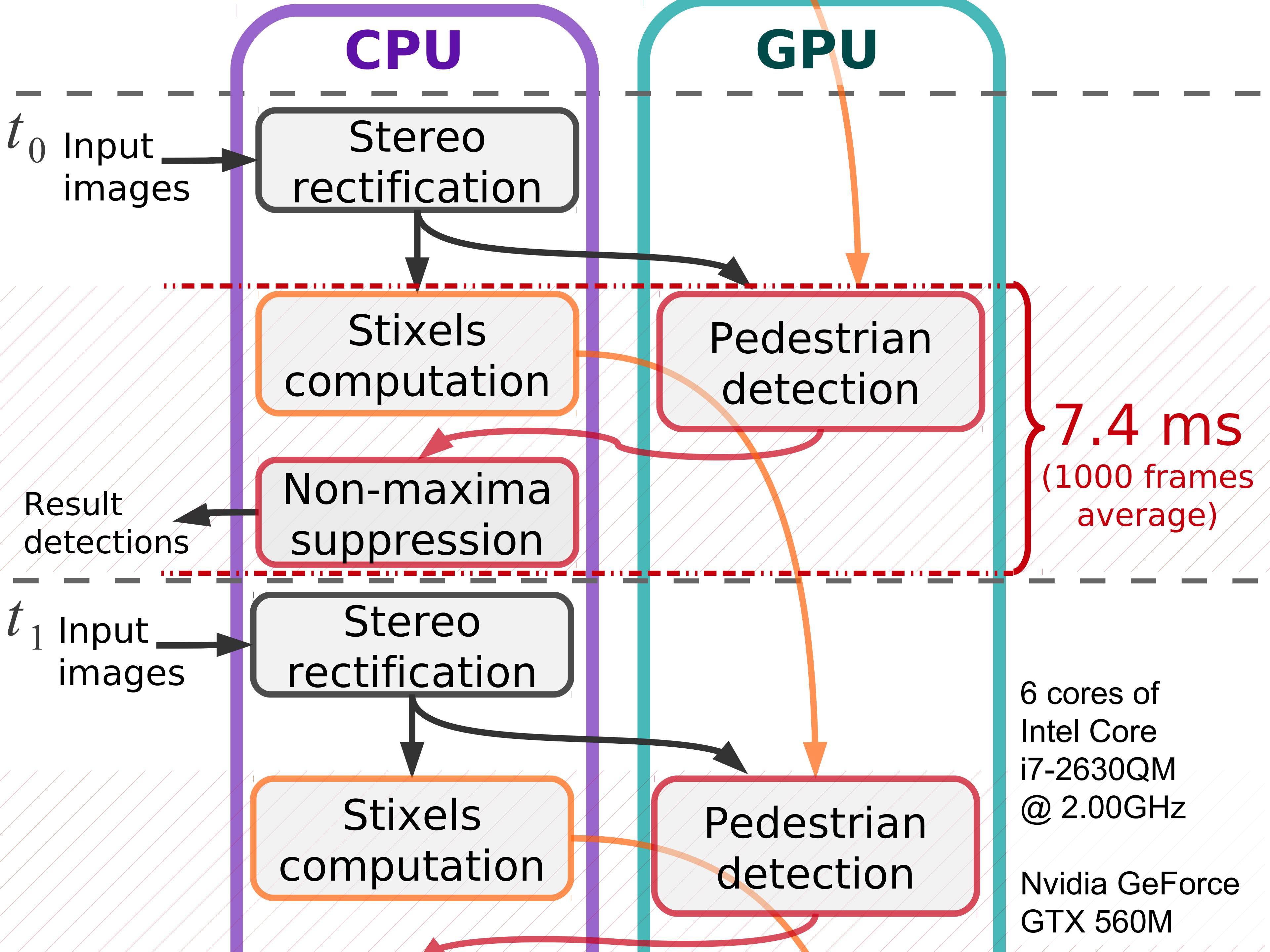
VISICS


CPU
GPU
t_0 Input images
Stereo rectification
Stixels computation
Pedestrian detection
Non-maxima suppression
Result detections
7.4 ms
(1000 frames average)
t_1 Input images
Stereo rectification
Stixels computation
Pedestrian detection
6 cores of Intel Core i7-2630QM @ 2.00GHz
Nvidia GeForce GTX 560M